ENEE698A : Deep Learning Seminar

Spatial Pyramid Pooling in Deep Convolutional Networks for Visual recognition

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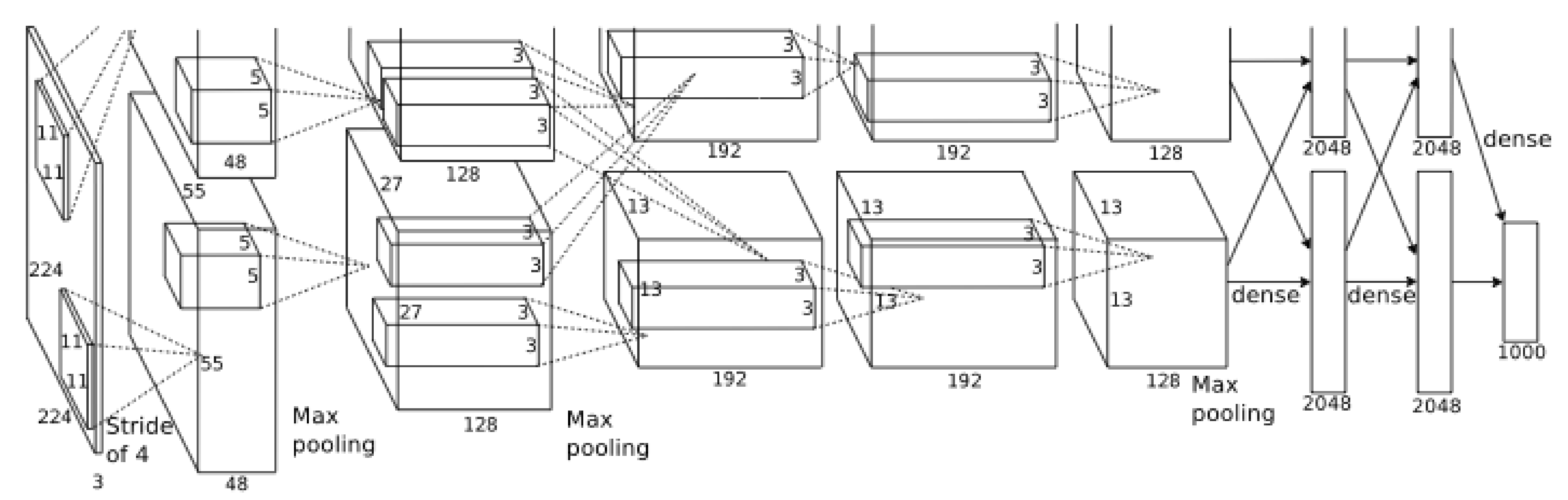
Deep CNN

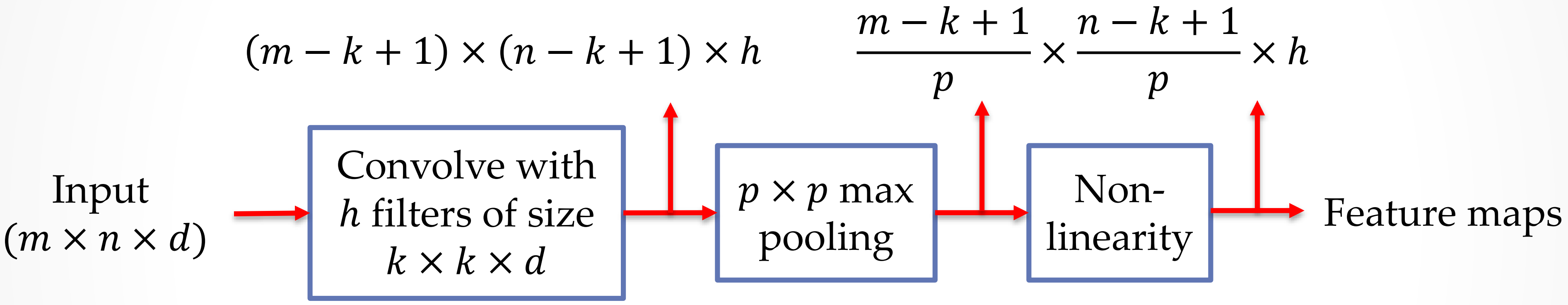


Input

Convolutional layers

Fully connected layers

Convolutional layer



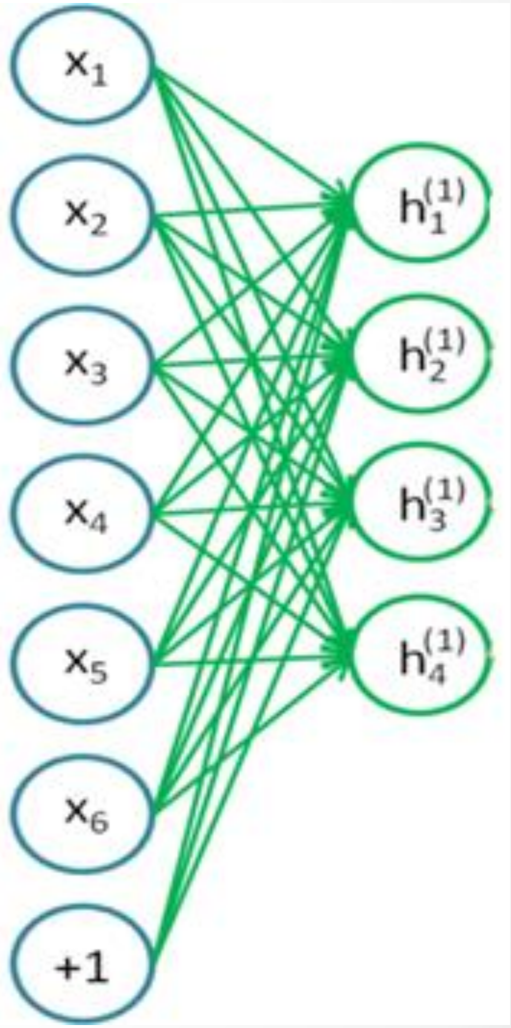
Size of the feature maps depends on the size of input for a given network.

Convolutional layers can be applied to input images of any size.

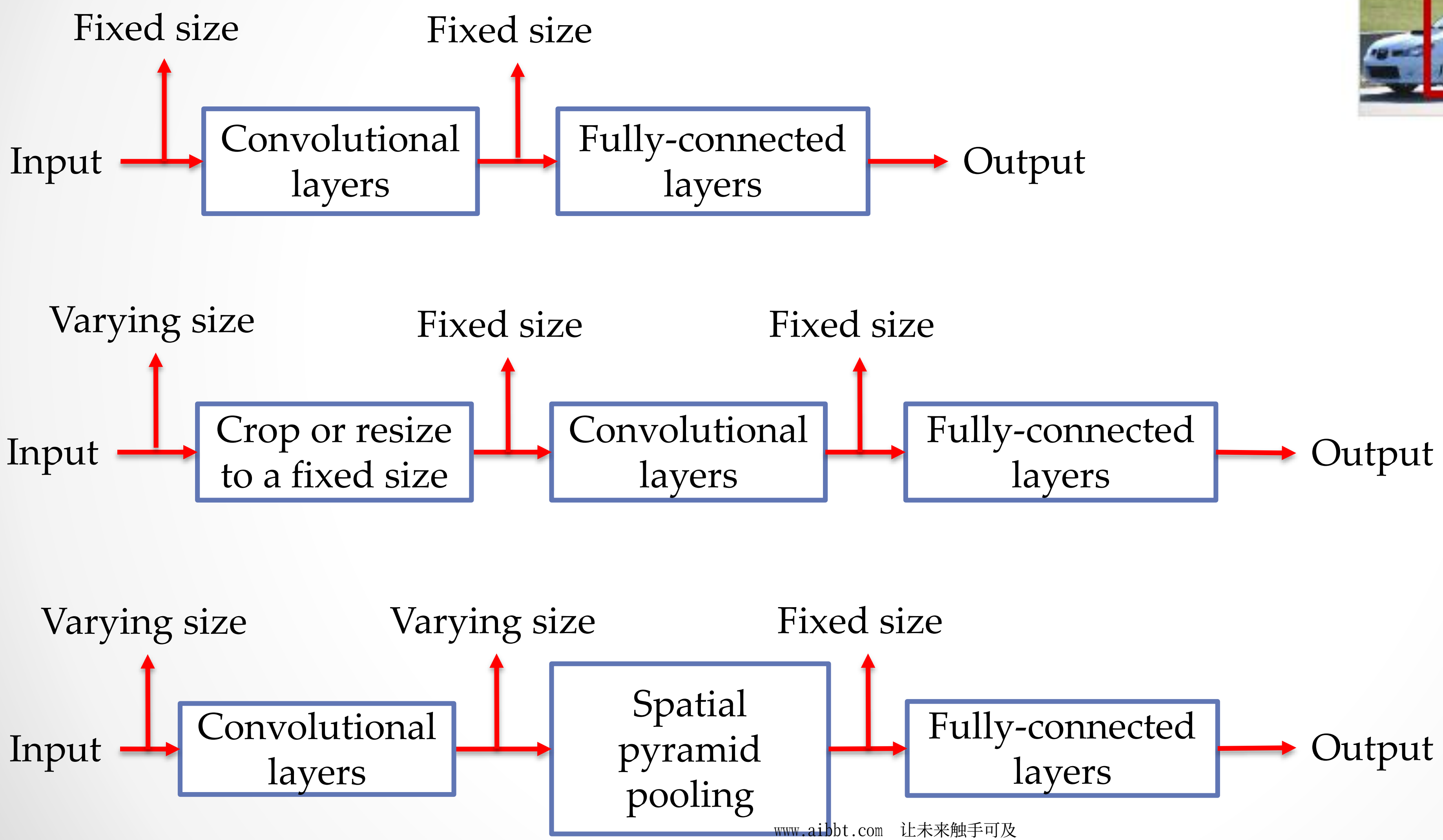
Fully connected layers

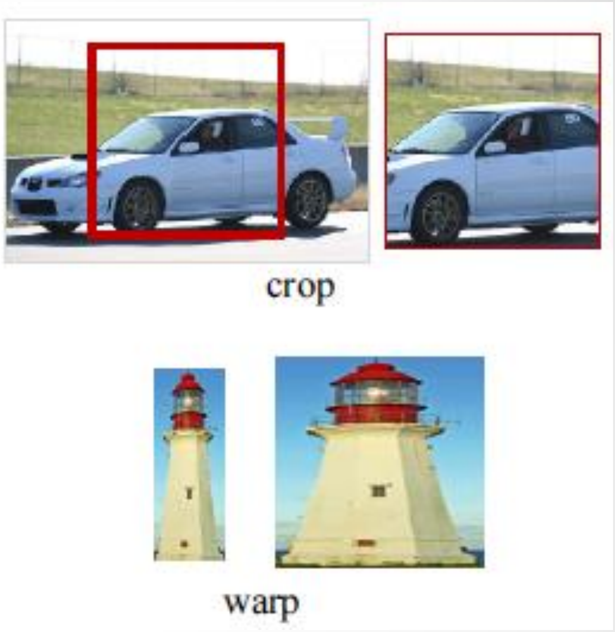
Fully connected layers require a fixed size input.

They cannot be applied to images of different sizes.



Size requirements





Pooling

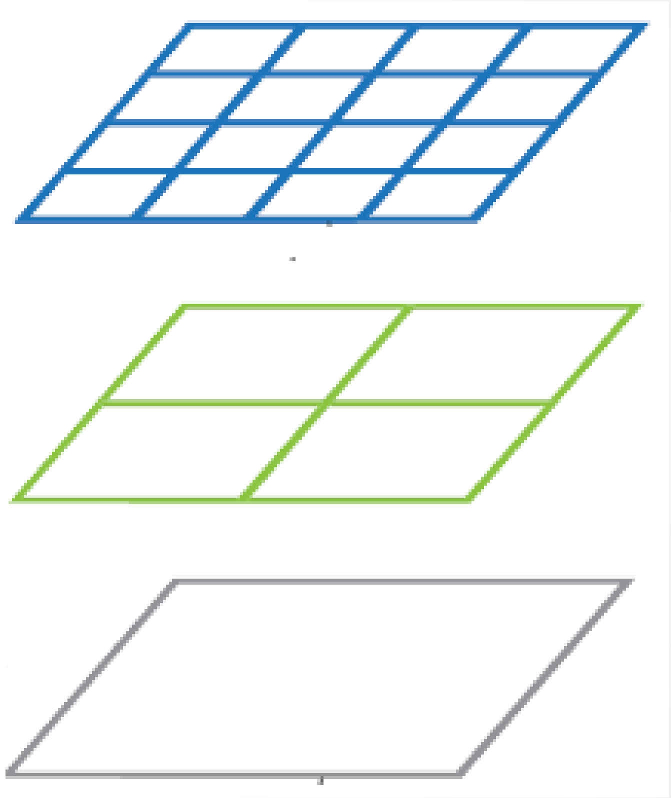
- Pooling function: Generates an aggregated representation for a set of features vectors $\left\{\overrightarrow{f_i}\right\}_{i=1}^{N}$.
  - Average pooling: $\frac{1}{N}\sum_{i=1}^{N}\overrightarrow{f_i}$.
  - Max pooling: Element-wise maximum
  - Second-order pooling: $\frac{1}{N}\sum_{i=1}^{N}\overrightarrow{f_i}\,\overrightarrow{f_i}^T$.

- The size of the pooling output does not depend on the number of features *N*.

Spatial pyramid pooling

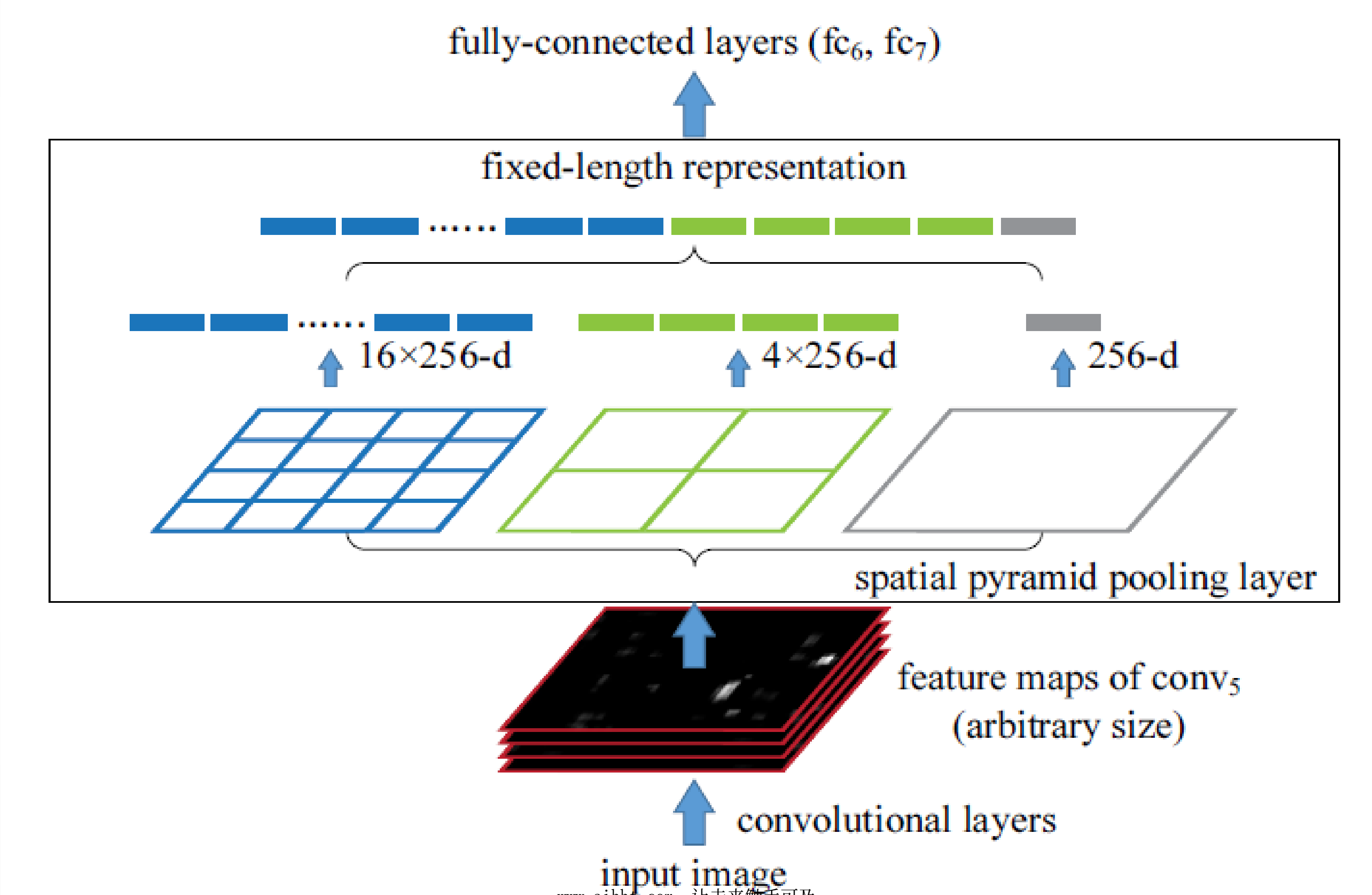
- Introduced in [Lazebnik 2006].

- Three steps:
  - Extract local feature descriptors at each pixel.
  - Divide the image into cells of different sizes.
  - Apply pooling function to each cell and concatenate all the pooling outputs.



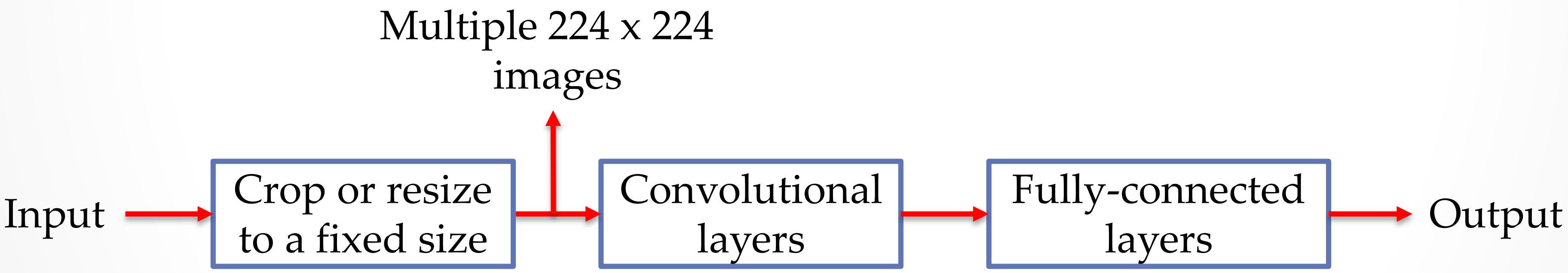
S. Lazebnik, C.Schmid, and J.Ponce, "Beyond bags of features: Spatial pyramid matching for recognizing natural scene categories", CVPR 2006.

Spatial Pyramid Pooling in CNNs

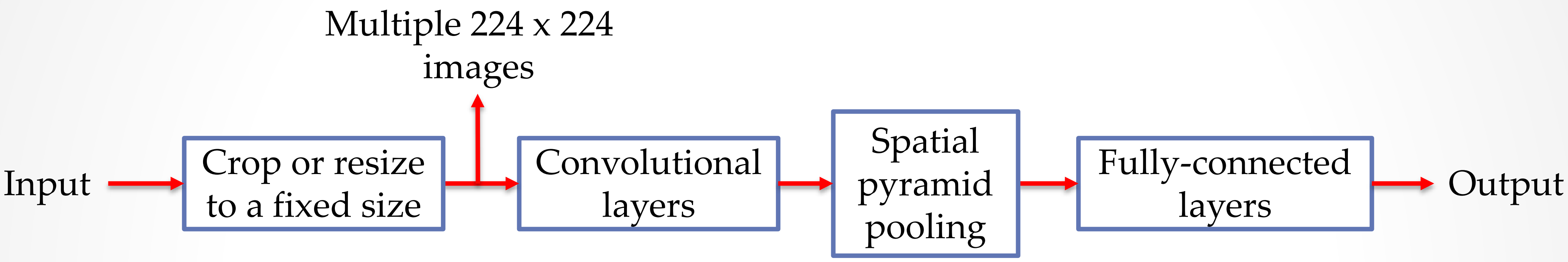


Experiments on ImageNet 2012

- Experimented with three different CNN architectures.
  - ZF-5 ([Zeiler 2013], 5 convolutional layers)
  - Convenet-5 ([Krizhevsky 2012], 5 convolutional layers)
  - Overfeat-5/7 ([Sermanet 2013], 5/7 convolutional layers)



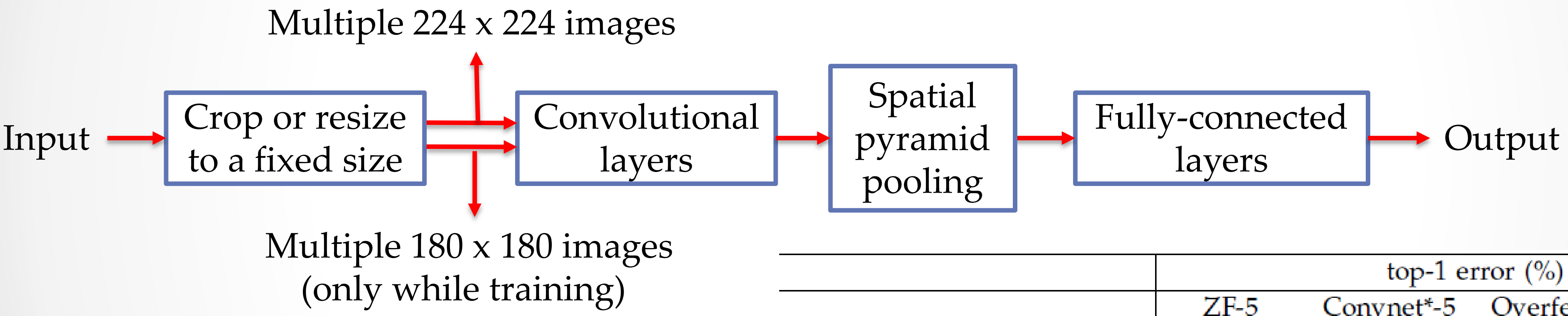
Spatial pyramid pooling improves accuracy



	top-1 error (%)			
	ZF-5	Convnet*-5	Overfeat-5	Overfeat-7
(a) no SPP	35.99	34.93	34.13	32.01
(b) SPP	34.98 (1.01)	34.38 (0.55)	32.87 (1.26)	30.36 (1.65)
	top-5 error (%)			
	ZF-5	Convnet*-5	Overfeat-5	Overfeat-7
(a) no SPP	14.76	13.92	13.52	11.97
(b) SPP	14.14 (0.62)	13.54 (0.38)	12.80 (0.72)	11.12 (0.85)

Multiscale training improves accuracy

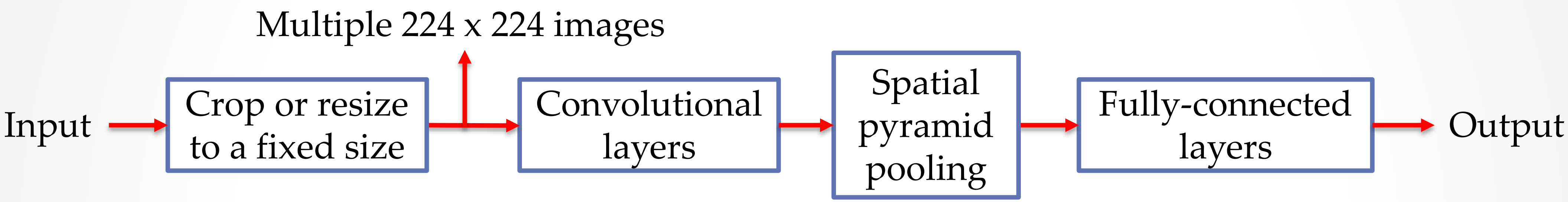
- Training with two sizes (224x224, 180x180), testing with 224x224 images.

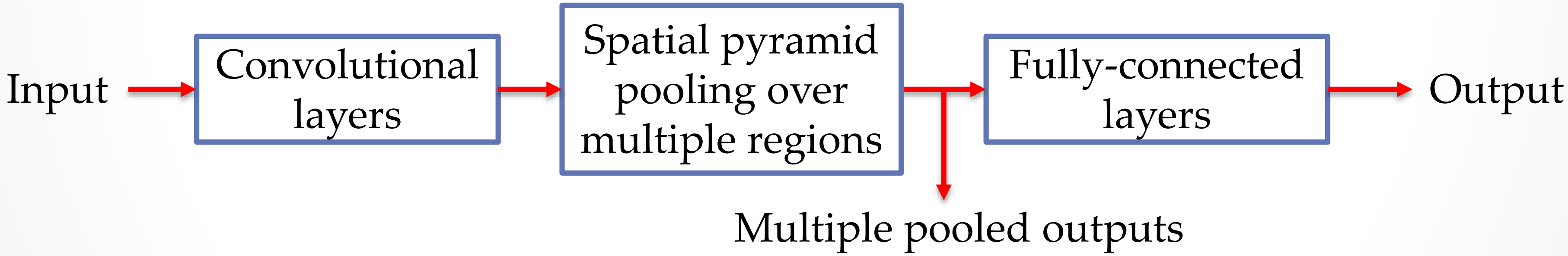


		top-1 error (%)			
		ZF-5	Convnet*-5	Overfeat-5	Overfeat-7
(a)	no SPP	35.99	34.93	34.13	32.01
(b)	SPP single-size trained	34.98 (1.01)	34.38 (0.55)	32.87 (1.26)	30.36 (1.65)
(c)	SPP multi-size trained	34.60 (1.39)	33.94 (0.99)	32.26 (1.87)	29.68 (2.33)

		top-5 error (%)			
		ZF-5	Convnet*-5	Overfeat-5	Overfeat-7
(a)	no SPP	14.76	13.92	13.52	11.97
(b)	SPP single-size trained	14.14 (0.62)	13.54 (0.38)	12.80 (0.72)	11.12 (0.85)
(c)	SPP multi-size trained	13.64 (1.12)	13.33 (0.59)	12.33 (1.19)	10.95 (1.02)

Reducing computation time





Much faster than applying convolutional layers to multiple images.

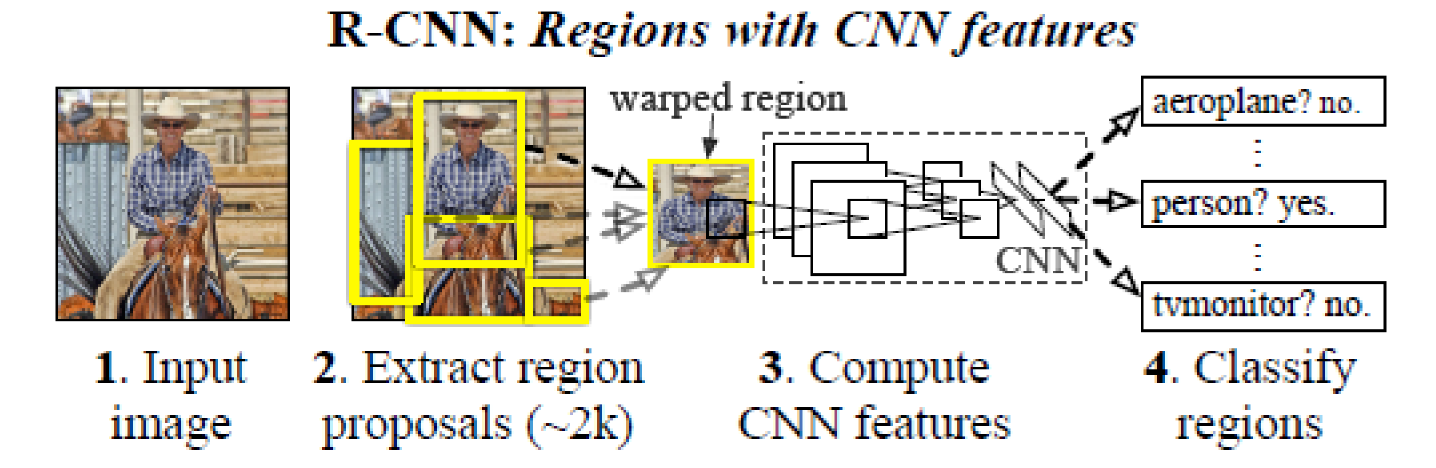
Multiscale network results

- Resized each image to six different scales.
- Applied CNN with SPP to six images.
- For each scale, SPP was applied to multiple regions in the final feature maps.
- A total of 98 different outputs were obtained from each image.
- Final result was based on the average of 98 outputs.

method	test scales	test views	top-1 val	top-5 val	top-5 test
Krizhevsky *et al.* [3]	1	10	40.7	18.2	
Overfeat (fast) [5]	1	-	39.01	16.97	
Overfeat (fast) [5]	6	-	38.12	16.27	
Overfeat (big) [5]	4	-	35.74	14.18	
Howard (base) [32]	3	162	37.0	15.8	
Howard (high-res) [32]	3	162	36.8	16.2	
Zeiler & Fergus (ZF) (fast) [4]	1	10	38.4	16.5	
Zeiler & Fergus (ZF) (big) [4]	1	10	37.5	16.0	
Chatfield *et al.* [6]	1	10	-	13.1	
ours	1	10	29.68	10.95	
ours	6	96+2full	**27.86**	**9.14**	**9.08**

Detection on PascalVOC 2007 using RCNN

- Generate 2000 object proposals using selective search.
- Resize each region into a pre-defined size (227x227).
- Extract features from each region using a deep CNN.
- Classify these features using SVM detectors.
- Runs CNN 2000 times.

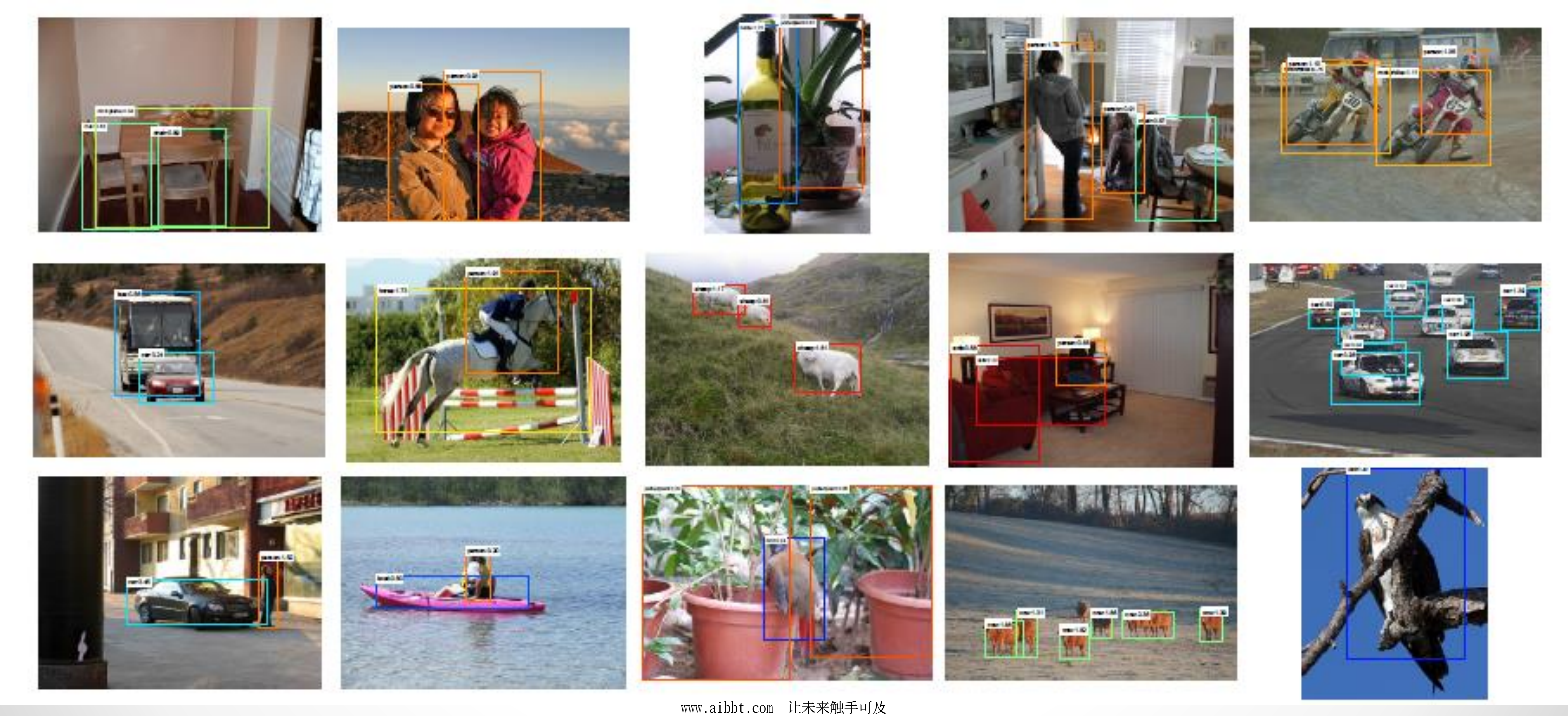


Detection using CNN+SPP

- Run convolutional layers on the entire image only once.
- Generate 2000 object proposals using selective search.
- Map each object proposal region in the input image to the corresponding region in the output of final convolutional layer.
- Use SPP to extract features from the final convolutional layer for each object proposal.
- Classify these features using SVM detectors.

mAP	58.0	58.5
conv time (GPU)	0.053s	8.96s
fc time (GPU)	0.089s	0.07s
total time (GPU)	0.142s	9.03s
speedup (*vs.* RCNN)	64×	-

Detection resutls



Thank You